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A potential control strategy for atmospheric particulate pollution based on power big data

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Abstract: With rapid economic development and urbanization, many cities, particularly in China, face serious PM_{2.5} pollution issues. In this study, the city of Hefei is selected as the research area to investigate the factors influencing PM_{2.5} concentrations. Data on electricity consumption of major PM_{2.5}-emitting industries, meteorological factors (temperature, wind speed, wind direction, relative humidity), and atmospheric pollutant concentrations (NO₂, SO₂, O₃, CO) are utilized to explore PM_{2.5} concentrations in Hefei from 2020 to 2021 using a generalized additive model (GAM). The aims are to identify the main influencing factors and potential control pathways for particulate matter pollution. Results reveal that CO accounts for 69% of the variation in PM_{2.5} mass concentration, suggesting it as the dominant factor in Hefei in 2020. Additionally, the major PM_{2.5}-emitting industries contribute to a 16% change in PM_{2.5} mass concentration, with a significant impact from smelting industries, which exhibit an increase in electricity consumption associated with an increase in PM_{2.5} mass concentration. Model fitting indicates that a 50% reduction in electricity consumption within the iron and steel making industries can lead to a 37% decrease in PM_{2.5} mass concentration compared to pre-reduction levels. Moreover, targeted control measures in winter result in higher reductions in PM_{2.5} pollution within a 40% reduction compared to consistent emission reductions throughout the year. These findings highlight the effectiveness of more focused control strategies based on localized circumstances. Implementing measures to restrict electricity use by key industries during high pollution seasons and in cities with high pollution levels can effectively address local PM_{2.5} pollution concerns.

Keywords: big data for electricity, GAM, PM_{2.5} influencing factors, PM_{2.5} potential control pathways

1. Introduction

PM_{2.5} refers to fine particulate matter in the atmosphere, characterized by an aerodynamic equivalent diameter of 2.5 μm or less. As they are extremely small and light, PM_{2.5} particles can persist in the atmosphere for extended periods and can be transported over long distances by atmospheric circulation, resulting in widespread air pollution [1]. Additionally, PM_{2.5} can cause reduced visibility and lead to hazy weather in urban areas [1]. Furthermore, PM_{2.5} plays a significant role in the global climate by influencing cloud formation and rainfall processes, thereby indirectly contributing to climate change. Moreover, this fine particulate matter is also able to enter the human alveolar, posing a great threat to human health, and is therefore also known as lung-borne particulate matter [2,3]. Consequently, PM_{2.5} has emerged as one of the prominent air pollutants causing widespread concern.

Variations in PM_{2.5} mass concentration are related to other air pollutants, local meteorological factors and industrial emissions [4–6]. Many city-scale studies have been conducted to investigate the relationship between PM_{2.5} and its influencing factors and predict its mass concentration changes using different models. Certain researchers have used VAR model to analyze the dynamic relationship between PM_{2.5} and various air pollutants and meteorological factors, and found that various air pollutants and meteorological factors

have different degrees of influence on $PM_{2.5}$ in various periods [7]. In addition, scholars have used multi-scale geographically weighted regression (MGWR) model to study the influence of local spatial and temporal effects on $PM_{2.5}$ in China [8]. Moreover, building upon these studies, other scholars have obtained a regression formula for $PM_{2.5}$ concentration [9]. It has been shown that the components and sources of $PM_{2.5}$ are complex, and the influence of meteorological factors also includes complex physicochemical processes. Consequently, it is necessary to consider the intricate non-linear relationship between $PM_{2.5}$ mass concentration and the influencing factors [10]. However, current studies on the influencing factors of $PM_{2.5}$ at urban scale generally only consider the linear relationship between $PM_{2.5}$ and the influencing factors, often ignoring the complex non-linear relationships between different variables. The generalized additive model (GAM), a statistical model often applied in environmental studies, is a semi-parametric extension of the generalized linear model (GLM). Compared with other models, the GAM can directly deal with the complex non-linear relationships between the response variables and multiple explanatory variables, and is therefore well suited to explain the non-linear relationships between $PM_{2.5}$ and its influencing factors, and further based on the model results to prediction of $PM_{2.5}$ concentrations [11,12].

Among the influencing factors of $PM_{2.5}$, industrial emissions are one of the important factors causing $PM_{2.5}$ pollution [4], and electricity consumption data can reflect the production implementation of enterprises, which also contains the enterprise $PM_{2.5}$ emission status [13–15]. Currently, electricity big data is extensively utilized across numerous domains, including electricity production, operational management, quality service, and smart cities [16–18], but there are few studies to apply electricity data to pollution analysis. Using the historical electricity consumption data of key $PM_{2.5}$ emitting enterprises can well reflect the $PM_{2.5}$ emission status of industrial sources. Combining the high temporal resolution industry electricity consumption data into the pollution analysis of $PM_{2.5}$ can provide a new perspective for us to study the influencing factors of $PM_{2.5}$.

This study aims to investigate the primary influencing factors of atmospheric $PM_{2.5}$ particulate matter in Hefei city from 2020 to 2021 by focusing on the electricity consumption data from major $PM_{2.5}$ emitting industries, as well as meteorological factors (temperature, wind speed, wind direction, relative humidity) and mass concentrations of atmospheric pollutants (NO_2 , SO_2 , O_3 , CO). The investigation will be conducted using the generalized additive model (GAM). Additionally, the study aims to examine the potential pathways for controlling particulate matter pollution by utilizing the GAM model constructed with electricity big data.

2. Study area, data and methods

2.1. Study area

Hefei, the capital of Anhui Province in China, is located in the mid-latitude zone, with four distinct seasons, a mild climate and moderate rainfall. The topography is complex and varied, with three types of land forms: plains, mountains and hills.

2.2. Sources of data

2.2.1. Sources of data on atmospheric pollutants

The data on atmospheric pollutant concentrations in Hefei from 1 January 2020 to 19 May 2021 analyzed in this study were obtained from the Ministry of Ecology and Environment (<http://sthjt.ah.gov.cn/site/tp1/5371>, whose data are published by the Anhui Ecological and Environmental Monitoring Centre) and include $PM_{2.5}$ ($\mu g/m^3$), NO_2 ($\mu g/m^3$), SO_2 ($\mu g/m^3$), CO (mg/m^3) and O_3 ($\mu g/m^3$) near ground mass concentration data at hourly resolution.

2.3. Meteorological data sources

Hourly meteorological data for the same period corresponding to the above air pollutant data were obtained from the National Oceanic and Atmospheric Administration website (<http://www.cdc.noaa.gov>, hereafter referred to as the NOAA website) and include temperature (T) ($^{\circ}C$), relative humidity (RH) (%), Wind speed (WS) (m/s) and wind direction (WD) ($^{\circ}$).

2.3.1. Sources of electricity consumption data for major PM_{2.5} emitting industries in Hefei

The list of major PM_{2.5} emitting enterprises in Hefei and their hourly electricity consumption data (Kw-h) for the same period corresponding to the above air pollutant data were provided by the State Grid Anhui Electric Power Company, which classified the above major PM_{2.5} emitting enterprises into nine categories of industries, and their classification and abbreviations are shown in Table 1. All electricity consumption data were subject to strict quality control to ensure completeness and representativeness, resulting in 94,059 valid data.

Table 1. List of major emitters in Hefei and their corresponding abbreviations

List of major emitters in Hefei	Abbreviations
Iron making	ELE1
Steel making	ELE2
Rare earth metal smelting	ELE3
Oil, coal and other fuel processing industries	ELE4
Non-metallic mineral products industry	ELE5
Chemical raw material and chemical product manufacturing	ELE6
Textile industry	ELE7
Rubber and plastic products industry	ELE8
Metal products industry	ELE9

2.4. Research methodology

A generalized additive model (GAM) is a non-linear regression framework and a semi-parametric extension of the generalized linear model (GLM) that can capture complex non-linear relationships between a response and multiple explanatory variables. We fitted the models using the *mgcv* package in R [12,19,20]. The basic form is

$$g(\mu) = \alpha + \sum_{i=1}^n f_i(x_i), \quad (1)$$

where μ denotes the expected value of the response variable (PM_{2.5} concentration), x_i ($i = 1, 2, \dots, n$) are the predictors, and $f_i(\cdot)$ are the corresponding smoothing functions. Model adequacy was assessed using the Akaike Information Criterion (AIC) and R^2 [21]. We used the F-statistic, associated p -value, and adjusted R^2 reported by the GAM to determine the significance of each explanatory variable's effect on PM_{2.5} and the overall goodness of fit: larger F-statistics indicate greater relative importance; smaller p -values indicate more statistically significant effects; and adjusted R^2 ranges from 0 to 1, with values closer to 1 indicating a better fit and higher explained variance [12,22]. All figures were produced with OriginPro 2022.

3. Results and discussion

3.1. Timing distribution characteristics of Hefei from 2020 to 2021

3.1.1. Annual air quality concentration profile for Hefei city, 2020-2021

The annual average PM_{2.5} mass concentration in Hefei from 2020 to 2021 is $34.28 \mu\text{g}/\text{m}^3$, which complies with China's secondary ambient air quality standard ($<35 \mu\text{g}/\text{m}^3$) [23]. However, it still falls below the recently updated WHO 2021 standard ($5 \mu\text{g}/\text{m}^3$) [24]. Figure 1 illustrates that in 2020, the average daily mass concentration of PM_{2.5} exceeded the Chinese standard for 9.7% of the year. Compared with the analytical data of PM_{2.5} in Hefei in previous years [25], the annual average PM_{2.5} mass concentration decreased from $61.60 \mu\text{g}/\text{m}^3$ in 2015 to $34.28 \mu\text{g}/\text{m}^3$ in 2020, and the PM_{2.5} daily average mass concentration exceedance rate decreased to 9.7%. This signifies an improvement. Nevertheless, it still surpasses 18.2% when compared to China's national average annual PM_{2.5} mass concentration in 2020 ($29 \mu\text{g}/\text{m}^3$) [23]. Furthermore, when juxtaposed with cities known for their superior air quality like Zhangjiakou [23], Hefei's PM_{2.5} pollution remains comparatively more severe.

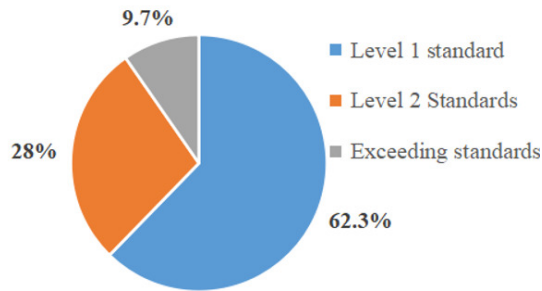


Figure 1. Distribution of daily average PM_{2.5} mass concentration in Hefei in 2020

3.1.2. Characteristics of monthly and seasonal changes in atmospheric quality concentrations in Hefei from 2020 to 2021

As shown in Figure 2, the monthly average PM_{2.5} mass concentrations in Hefei exceeded China's national ambient air quality secondary standards for a total of three months (January, November and December) in 2020, an improvement compared to previous years [25]. The monthly mean PM_{2.5} mass concentrations in Hefei City exhibit a consistent pattern of decrease followed by increase throughout the year, indicating higher levels during winter and lower levels during summer. December 2020 recorded the highest monthly mean PM_{2.5} mass concentration of $74.15 \mu\text{g}/\text{m}^3$, while the lowest values were observed in June and August, which are summer months. The average winter PM_{2.5} mass concentration in Hefei in 2020 is 65.6% higher than the annual level, signifying a more severe atmospheric PM_{2.5} pollution during winter.

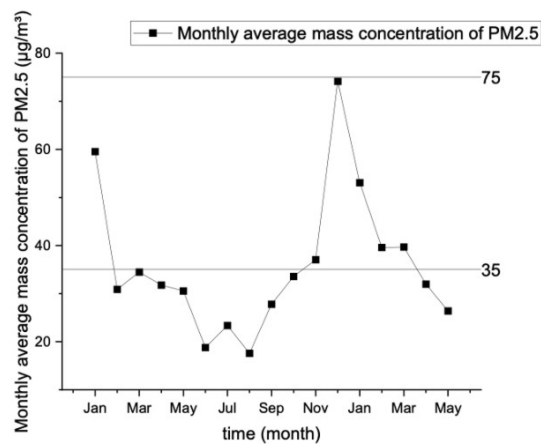


Figure 2. Monthly average PM_{2.5} mass concentration in Hefei from January 2020 to May 2021 as a function of time

3.2. Analysis of electricity consumption data for the main PM_{2.5} emitting industries from 2020 to 2021

According to Figure 3, the electricity consumption of most industries (excluding the ELE4 industry) from 2020 to 2021 showed an upward trend. Specifically, ELE1, ELE3, and ELE5 industries experienced a significant increase in electricity consumption during the autumn and winter seasons, suggesting a recent rise in industrial electricity consumption in Hefei. This trend is further supported by the data in Table 2. The ELE5 and ELE6 industries exhibited the highest average daily electricity consumption during 2020-2021, reaching 2.91×10^6 Kw-h and 2.66×10^6 Kw-h respectively. Conversely, the ELE2 and ELE4 industries had the lowest average daily electricity consumption compared to other industries from 2020 to 2021, at 6.07×10^4 Kw-h and 1.18×10^4 Kw-h respectively.

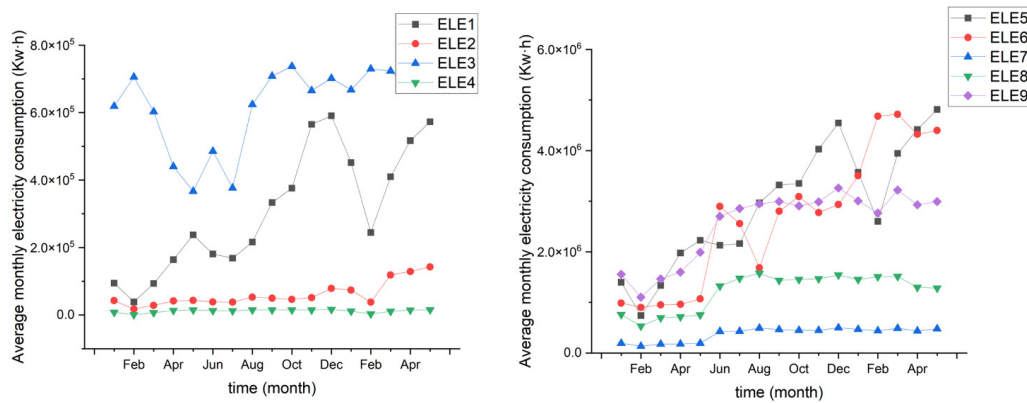


Figure 3. Monthly average daily electricity consumption by sector over time

Table 2. Growth rate of average daily electricity consumption of major PM_{2.5} emitting industries in Hefei in the first half of 2021 from January to May compared to the same period in 2020

List of major emitters in Hefei	Growth rate
ELE1	249%
ELE2	189%
ELE3	28%
ELE4	25%
ELE5	152%
ELE6	344%
ELE7	164%
ELE8	104%
ELE9	93%

3.3. GAM fitting results

The initial selection of temperature (T) as the explanatory variable for PM_{2.5} was fitted with the GAM model, and then variables were gradually added to the model, of which all passed the significance test ($p < 0.001$) except WS ($p = 0.279$), which failed the significance test and was excluded.

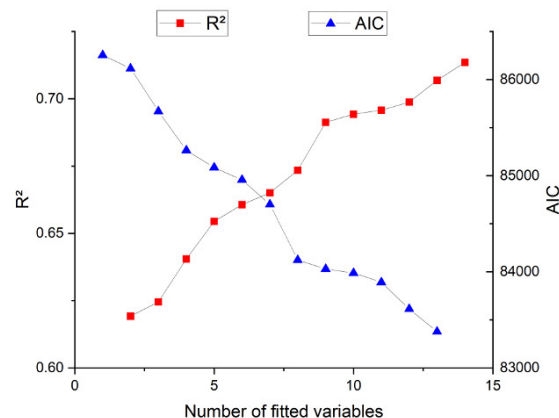


Figure 4. Plot of R^2 value, AIC value and number of fitted variables of the fitted function

The AIC and R^2 values for each variable added were plotted (Figure 4), which showed that as the number of variables increased the AIC value decreased and the R^2 value increased, indicating that all the variables added were valid [26], with the addition of the rubber and plastic products and metal products variables not meeting the decreasing AIC and increasing R^2 values and being excluded. The final model equation is $g(\text{PM}_{2.5}) = s(\text{CO}) + s(\text{T}) + s(\text{NO}_2) + s(\text{SO}_2) + s(\text{ELE2}) + s(\text{ELE1}) + s(\text{ELE3}) + s(\text{ELE4}) + s(\text{ELE5}) + s(\text{ELE6}) + s(\text{ELE7}) +$

$s(RH) + s(WD) + s(O_3) + \varepsilon$. In general, when the adjusted R^2 value exceeds 0.5, the GAM model is considered to explain the response variable well [27], and this model has an R^2 value of 0.7163 (Figure 5), indicating a good model fit.

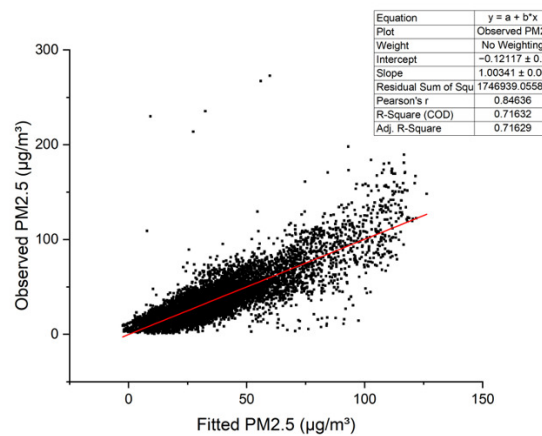


Figure 5. Relationship between observed $PM_{2.5}$ mass concentrations and fitted $PM_{2.5}$ mass concentrations

3.4. GAM-based factors influencing $PM_{2.5}$

3.4.1. General characteristics

As can be seen from Table 3, the final 14 fitted variables all had a statistically significant effect on the change in $PM_{2.5}$ mass concentration at the $P < 0.001$ level, i.e. all 14 influencing factors were statistically significant as explanatory variables for $PM_{2.5}$ mass concentration alone.

Table 3. F-values, P-values and impact percentages corresponding to each fitted variable, the larger the F-statistic value corresponding to the influencing factor, the greater its relative importance; P-value is another parameter used to judge the hypothesis test result, the smaller the P-value, the more significant the result; *** indicates that the variable is significant at the 0.001 level

Fitting variables	F-values	P-values	Percentage of impact
CO	659.88	$<2e-16$ ***	69.3%
ELE2	53.37	$<2e-16$ ***	5.6%
O ₃	48.034	$<2e-16$ ***	5.0%
WD	38.231	$<2e-16$ ***	4.0%
ELE5	33.921	$<2e-16$ ***	3.6%
ELE1	23.823	$<2e-16$ ***	2.5%
NO ₂	19.463	$<2e-16$ ***	2.0%
SO ₂	17.531	$<2e-16$ ***	1.8%
ELE6	11.587	$<2e-16$ ***	1.2%
T	11.343	$<2e-16$ ***	1.2%
ELE3	10.608	$<2e-16$ ***	1.1%
RH	10.324	$<2e-16$ ***	1.1%
ELE4	8.383	$<2e-16$ ***	0.9%
ELE7	5.918	$<2e-16$ ***	0.6%

CO (69.3% influence), O₃ (5.0% influence), WD (4.0% influence), ELE1 - Ironmaking (2.5% influence), ELE2 - Steelmaking (5.6% influence) and ELE5 - Non-metallic Mineral Products (3.6% influence) were the five fitted variables with larger F-values in the GAM model and the model was fitted well, i.e. the effect of CO, O₃, WD, ELE1 (Ironmaking), ELE2 (Steelmaking) and ELE5 (Non-metallic Mineral Products) individually as explanatory variables had a significant effect on the change in mass concentration. The influence of CO on the change of $PM_{2.5}$ mass concentration is 69% in the GAM, indicating that CO is the dominant influence on

the change of $\text{PM}_{2.5}$ mass concentration in Hefei in 2020. The influence of major $\text{PM}_{2.5}$ emitting industries on the change of $\text{PM}_{2.5}$ mass concentration is 16% in the model, indicating that industrial emissions are also the influence on the change of $\text{PM}_{2.5}$ mass concentration. $\text{PM}_{2.5}$ mass concentration change is one of the important factors.

3.4.2. Main pollutants and meteorological factors versus mass concentration GAM fit

From Figure 6, the variables CO, O_3 , and $\text{PM}_{2.5}$ display a positive correlation, suggesting that an increase in CO and O_3 is significantly associated with an increase in $\text{PM}_{2.5}$ mass concentration. One possible explanation for the strong correlation between $\text{PM}_{2.5}$ and O_3 is that O_3 , a potent oxidant, can oxidize substances in the air thereby generating aerosols and acid mists. These particles, in turn, attract more dust and heavy metal ions, ultimately leading to an increase in $\text{PM}_{2.5}$ concentrations [28]. CO, on the other hand, is primarily emitted from fossil fuel and biomass combustion. Thus, one possible reason for the strong correlation between $\text{PM}_{2.5}$ and CO is that the major constituents of $\text{PM}_{2.5}$ result from primary emissions [29]. Additionally, primary pollutants like CO can undergo photochemical reactions, producing the secondary pollutant O_3 in the lower atmosphere, which further increases $\text{PM}_{2.5}$ concentrations [30]. Furthermore, it is observed that $\text{PM}_{2.5}$ slightly decreases as temperature rises above zero degrees Celsius, a pattern consistent with the higher levels of $\text{PM}_{2.5}$ during winter compared to summer. Moreover, small increases in SO_2 and NO_2 concentrations, as well as changes in relative humidity (RH), have minimal impact on $\text{PM}_{2.5}$ concentrations.

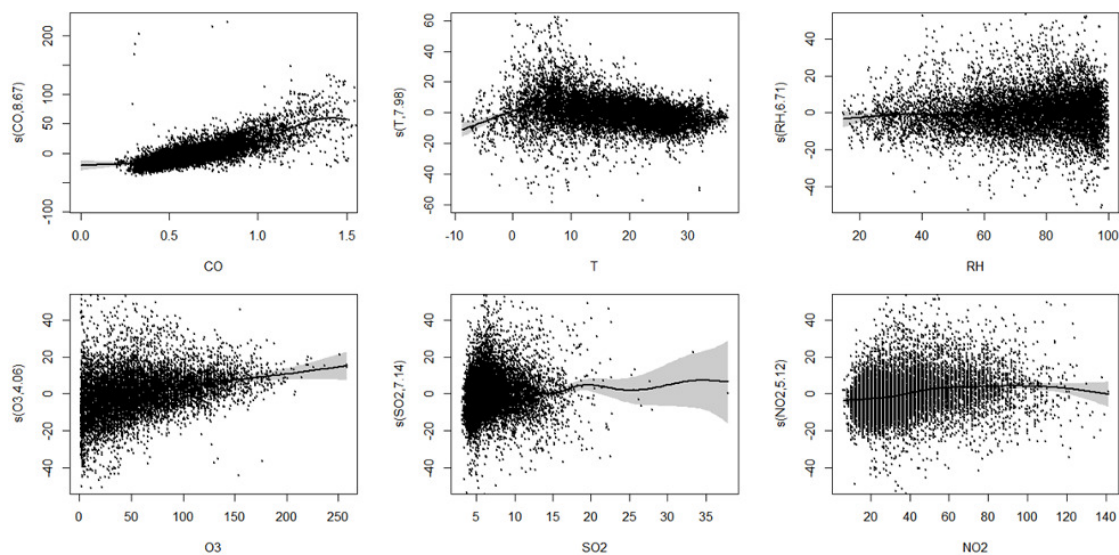


Figure 6. The effect of meteorological factors and pollutants on $\text{PM}_{2.5}$ in the GAM. The Y-axis in each subplot is the smoothing function term for the corresponding influence factor, the number in brackets represents its degree of freedom, and the X-axis is the distribution of the corresponding influence factor (corresponding to the scatter in the plot)

3.4.3. Big data and mass concentration GAM fit relationships for electricity in major emission sectors

According to Figure 7, $\text{PM}_{2.5}$ mass concentrations in iron making (ELE1) increase with electricity consumption below 18,000 Kw-h. Similarly, in steel making (ELE2), $\text{PM}_{2.5}$ mass concentrations rise with electricity consumption below 3,000 Kw-h. These findings suggest a correlation between increased electricity consumption and higher $\text{PM}_{2.5}$ mass concentrations in the smelting industry in Hefei. It is likely that the emission of $\text{PM}_{2.5}$ and related precursors from these industries is closely related to their production and electricity consumption processes. Implementing limits on electricity consumption can effectively control changes in $\text{PM}_{2.5}$ mass concentrations for these companies. Additionally, Figure 7 shows a negative correlation between the non-metallic mineral products industry (ELE5) and the change in $\text{PM}_{2.5}$ mass concentration. On the other hand, industries like rare earth metal smelting (ELE3) have a lesser impact on the change in $\text{PM}_{2.5}$

mass concentration. These kinds of enterprises should control their $PM_{2.5}$ emissions according to their specific circumstances.

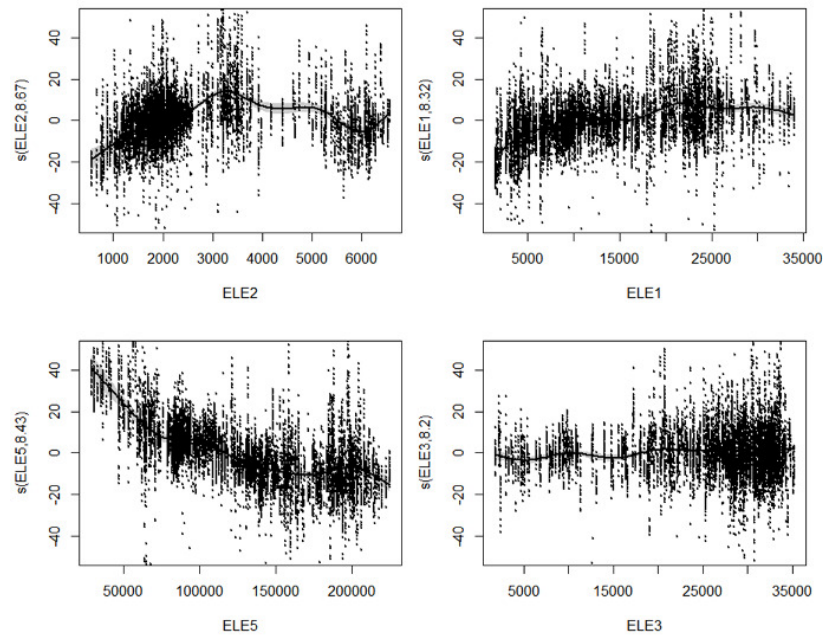


Figure 7. Plot of partial dependence between electricity consumption and $PM_{2.5}$ in key emission sectors in the GAM. The Y-axis in each subplot is the smoothing function term for the corresponding influence factor, the number in brackets represents its degree of freedom, and the X-axis is the distribution of the corresponding influence factor (corresponding to the scatter in the plot)

3.5. Potential pathways to control pollution based on electricity

Based on the constructed GAM model, we simulated the impact of reducing the electricity consumption of the ELE1 (iron making) and ELE2 (steel making) industries by 50% on $PM_{2.5}$. Figure 8 demonstrates that this reduction in key industries resulted in a significant decrease in $PM_{2.5}$ mass concentration, with a 37% reduction relative to the pre-reduction levels. The mass concentration was still 23% lower compared to before. Further reductions in electricity use in the ELE1 (iron making) and ELE2 (steel making) sectors, at varying degrees, shown in Figure 9, corresponded to an increasing $PM_{2.5}$ mass concentration reduction. For example, a 20% reduction in electricity use in the controlled ELE1 (iron making) and ELE2 (steel making) sectors resulted in a 10% reduction in $PM_{2.5}$ mass concentration. These results highlight the potential to greatly reduce $PM_{2.5}$ pollution by limiting electricity use in key emitting industries, as revealed by the GAM analysis.

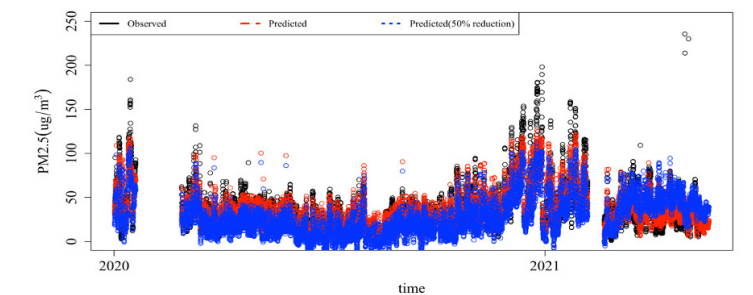


Figure 8. Plot of observed $PM_{2.5}$ mass concentration versus model predicted values over time, where black represents observed values, red represents model predicted values and blue represents predicted values for ELE1, ELE2 with 50% reduction in emissions

When considering the control of electricity consumption in the ELE1 (iron making) and ELE2 (steel making) industries exclusively during the high pollution season of winter (January, February, and December), Figure 9 demonstrates that reducing electricity consumption by 20%, 30%, and 40% correspondingly led to reductions in $PM_{2.5}$ mass concentration of 11%, 20%, and 27%. These reductions are comparable to those achieved over the entire year, signifying that limiting electricity use during high pollution seasons can yield significant results. Therefore, targeted control of high $PM_{2.5}$ pollution seasons can effectively reduce local $PM_{2.5}$ pollution. Based on the results of the GAM model, it is possible to implement more targeted measures for controlling $PM_{2.5}$ pollution in each city. Implementing restrictions on the use of electricity by key local industries during high pollution seasons and in heavily polluted cities can effectively control local $PM_{2.5}$ pollution.

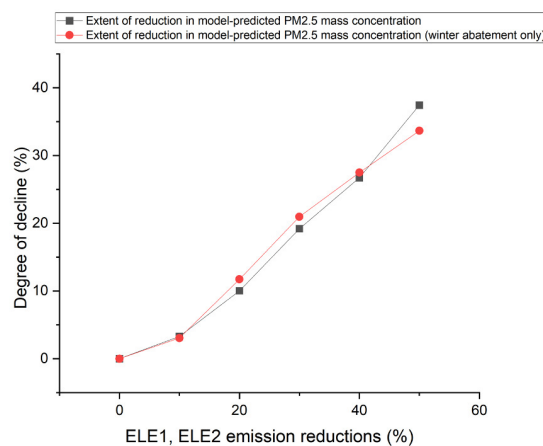


Figure 9. The relationship between emission reductions and pollution reduction for ELE1 (iron making) and ELE2 (steel making) industries with different levels of emission reductions

4. Conclusion

The analysis of the temporal distribution characteristics of $PM_{2.5}$ in Hefei from 2020 to 2021 reveals an improvement in $PM_{2.5}$ pollution control in recent years. However, the average $PM_{2.5}$ winter mass concentration in Hefei during this period is still 65.6% higher than the annual level, indicating the persistent severity of atmospheric $PM_{2.5}$ pollution in winter. This study utilizes a generalized additive model (GAM) to explore the main influencing factors of $PM_{2.5}$ particulate matter concentration in Hefei from 2020 to 2021, including electricity consumption data, meteorological factors, and air pollutant concentrations from major $PM_{2.5}$ emitting industries. Additionally, it examines potential paths for controlling particulate matter pollution.

The study reveals that CO exerts the most substantial influence on the change of $PM_{2.5}$ mass concentration in Hefei in 2020, accounting for 69% in the GAM model. This finding highlights the dominant role of CO as an influencing factor. Furthermore, the model indicates that major $PM_{2.5}$ emission industries contribute to a 16% change in $PM_{2.5}$ mass concentration, emphasizing the significance of industrial emissions as a factor driving $PM_{2.5}$ levels. Notably, smelting industries, such as iron and steel making, characterized by increased electricity consumption, are identified as having a sizable influence on the increase in $PM_{2.5}$ mass concentration.

Based on the model fitting results, a 50% reduction in electricity consumption in the ELE1 (iron making) and ELE2 (steel making) industries leads to a notable decrease in $PM_{2.5}$ mass concentration, with a 37% reduction after emission reduction compared to before. The reduction in $PM_{2.5}$ mass concentration increases significantly with the degree of reduction. These findings demonstrate the substantial potential for reducing $PM_{2.5}$ pollution by limiting the electricity consumption of key emitters according to the GAM analysis. Additionally, controlling electricity consumption in key emitting industries during the high pollution season of winter results in higher reductions in $PM_{2.5}$ pollution within a 40% reduction, as compared to reducing emissions in these industries throughout the year. This highlights the effectiveness of targeted control of $PM_{2.5}$ during high pollution seasons. The GAM model's results provide insights for implementing more targeted $PM_{2.5}$ pollution control measures in each city. Implementing restrictions on electricity use by key

local industries during high pollution seasons and in heavily polluted cities can effectively control local PM_{2.5} pollution.

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Data Availability: The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors have no relevant financial or non-financial interests to disclose.

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